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CHOOSING A METHOD FOR PREDICTING ECONOMIC PERFORMANCE OF COMPANIES

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This paper reports on the efforts to find a method for predicting economic results of companies. The input data files consist of 93 profitable companies and 93 bankrupt firms. From the total number of 93 firms in both categories, data of 72 firms served for establishing a classification criterion, and for the rest of 21 firms, a prognosis of their economic development was performed. The classification criterion for prognosticating the future economic development has been established by applications of discriminate analysis, logit analysis, and artificial neural network methods. The application of artificial neural networks has provided for better classification accuracies of 90,48 % for successful firms, and 100 % for bankrupt firms.

Key words: Prediction, Discriminant analysis, Logit analysis, Artificial neural networks, Classification accuracies

Izbor metode za predviđanje ekonomskih rezultata tvrtki. U ovom se članku opisuju pokušaji pronalaska učinkovite metode za predviđanje ekonomskog rezultata tvrtki. Datoteke ulaznih podataka sastoje se od 93 uspješne tvrtke i 93 tvrtke koje su bankrotirale. Od ukupnog broja od 93 tvrtke u obje kategorije datoteka s ulaznim podacima, podaci za 72 tvrtke poslužili su za određivanje klasifikacijskog kriterija a za preostalu 21 tvrtku provela se prognoza njihovog ekonomskog razvoja. Klasifikacijski kriterij za predviđanje budućeg ekonomskog razvoja tvrtke uspostavljen je primjenom analize diskriminacije, logičkom regresijom i metodama umjetne neuronske mreže. Primjena logičke regresije i umjetnih neuronskih mreža omogućila je bolju klasifikacijsku točnost u slučaju 90,48 % uspješnih tvrtki i 100 % tvrtki koje su bankrotirale.

Ključne riječi: predvidljivost, analiza razlika, analize logičke regresije (Logit analize), umjetne neuronske mreže, klasifikacija točnosti

INTRODUCTION

A prerequisite for the existence of companies in a free market economy is their ability to comply to agreements with co-operating partners, employees or the laws of the State, especially that of paying debts. There are various methods that can be used for predicting the future economic performance of companies.

The starting point consists in assembling files of successful (profitable) and unsuccessful (bankrupt) companies – so called 'application files'. Each company's performance can be characterized by indices deduced from their financial statement data. A specific method can provide for a criterion that would enable the classification of companies in so called 'testing files' as profitable or bankruptcy threatened.

This criterion has been used for the classification of our firms and it can be used for predictions of economic development of any other set of firms that are characterized by the same economic indices. The percentage of proper or wrong classification of testing files subjects is a measure of the accuracy of the method applied.

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This paper continues in the previous project work [1] that looked for indices, which would be best suited to evaluate economic performance of companies. Once these indices had been established, they were scrutinized by the discriminant analysis method, and a question was asked whether the discriminant analysis was the best method of classifying firms as successful or bankrupt.

The answer can be provided by many research papers that have investigated the problem.

Models to predict failure can be traced back to the 1930's using single indicators to conduct analyses. Until the 1980's, the multiple discriminant analysis (MDA) technique dominated the literature on business failure prediction.

Since the 1980's, the use of multiple discriminant analysis has decreased, but it remains a generally accepted standard method [2]. Multiple discriminant analysis still remains the most popular and most widely used failure prediction technique in the United Kingdom [3]. Over the past 30 years most researchers concentrated their efforts on building multivariate discriminatory models, using increasingly sophisticated procedures and applying them to different sets of independent variables [4].

However, the validity and effectiveness of MDA depend largely on some restrictive assumptions. To avoid the assumptions of MDA, Logistic Regression (Logit) Analysis, which has less restrictive assumptions, was used. Logistic regression (Logit) analysis is theoretically more appealing than discriminant analysis when criterion variables are binary [5]. Until now, Logit Analysis has been a very popular method in business failure prediction [2].

After the 1980's, scholars tried adopting different analytical techniques such as Neural Network Analysis (NNA) apart from traditional methods to find better classification tools in producing higher prediction accuracies [6].

A number of such models have been developed in recent years. Generally they perform at least as well as, and often slightly better than, more conventional statistically derived multivariate bankruptcy identification models [4], similarly [3,7,8].

While empirical studies show that artificial neural networks (ANN) produce better results for many classification or prediction problems, they are not always uniformly superior. It is reported disappointing findings in applying neural network for predicting commercial bank failures [8].

It is obvious that the research publication results in this area are not quite clear or they depend on conditions of individual states in which the research was conducted [3]. For that reason, it was decided to apply not only the discriminate analysis method but also the method of logistic regression and neural networks for predicting of economic performance of companies in the Czech Republic.

BACKROUND INFORMATION ON CHOOSING OF METHODS FOR PREDICTING ECONOMIC PERFORMANCE OF COMPANIES

Input files

The files of 93 successful and 93 bankrupt companies were assembled as follows: Bankrupt firms in time (t) were chosen at random from the list of bankrupt companies provided in the Business Register of the Czech Republic. The date of issue of financial statements must have been 12 months before their default notice at the longest, time, (t−1) at the end of the year. We also recorded the financial statement data a year before, i.e., time, (t–2). The successful firms in time (t) were selected on their then current and recent economic performances. The date of issue of the financial statements must not have been older than 12 months before our investigation, time, (t−1) at the end of the year. We also recorded the financial statement data a year before, i.e., time, (t−2).

This information provided for the input data of calculating relevant indices of the companies' performances, namely the indicators indexes as indicator values in time (t−1)/ (t−2).

The authors own the database on the successful and bankrupt firms. The time span of the database is 1996–2010. From the initial data file of 186 successful and default firms, 72 items in each category were used for applications of discriminate analysis, logistic regression and artificial neural network methods so that a criterion would be established that that could classify an individual firm as successful or default. The resting file of 42 firms (half successful, half default – testing file) was used for testing the accuracy of the classification criterion established.

The financial statements of companies provided for the establishment of economic indices that reflected their performance. Input indices employed:

No 1: Ratio, [total liabilities/ total assets], measure of indebtedness,

No 2: Index, [total liabilities, (t−1)/ total assets, (t−1)]/ [total liabilities, (t−2)/ total assets, (t−2)], measure of indebtedness development,

No 3: Current Assets Index, [current assets, (t−1)/ current assets, (t−2)], circulation of capital characteristics,

No 4: Production Index, [production, (t−1)/ production,(t−2)], characteristics of production activities,

No 5: Ratio, [financial assets/ current assets], reflects shares of the most liquid part of the property in currents assets,

No 6: Ratio, [current assets/ total assets], wealth structure characteristics,

No 7: Ratio, [sales of goods and services/ total assets], productivity characteristics,

No 8: Ratio, [current liabilities/ total assets], a connection with a firm's liquidity – debt payment characteristics.

Table 1 gives the average values of input data of 72 successful and 72 bankrupt companies (application files) and average values of 21 successful and 21 default firms of the testing file.

Table 1 **Average values of economic indicators**

	Application files		Testing files	
Indicator No	72 successful firms	72 bankrupt firms	21 successful firms	21bankrupt firms
1	0,39	2,01	0,34	3,36
2	0,87	1,77	0,90	1,34
3	1,24	0,74	1,04	0,74
4	1,33	0,97	1,37	0,56
5	0,33	0,10	0,39	0,04
6	0,51	0,57	0,62	0,61
7	1,52	1,56	1,12	1,67
8	0,19	1,47	0,19	2,81

APPLIED METHODS

Method of Discriminate Analysis

Discriminate analysis provides for the assessment of differences between two or more units characterized by several variables (so called discriminators).

In our case, the discriminators are the economic indices defined above. The output is the criterion value that enables the classification of units (firms) into groups of successful or default subjects.

Method of logistic regression (Logit analysis)

The logistic regression provides for an alternative method of classification if preconditions of multidimensional normality are not met. The resulting model of the logistic regression function can be also used for classification of other objects of which only values of independent variables are known. The method of logistic regression differs from the discriminate analysis in that it predicts probability of classification in relevant groups.

Method of Artificial Neural Networks

The concept of artificial neural networks is associated with a wide range of mathematical methods that have been inspired by neural networks of living organisms.

In the framework of these methods, a neuron makes for a constituting element of any artificial neural network. The neurons are interconnected into nodes and an interconnected group of nodes is an artificial neural network. Each neuron is defined by a specific mathematical equation with several 'internal' variables that along with the input values influence a neuron output value.

After structuring an artificial neural network and defining a neuron type, it is necessary to have it adapted to a given task. The artificial neural network must learn first. It must be subjected to training.

After training, the neural networks can be fed with data of units that have not been used for training, and the adapted and trained neural networks should deliver outputs providing for the classification of these new units.

RESULTS AND DISCUSSION

The input file of 93 successful and 93 default (officially bankrupt) firms was divided into 72+72 firms of the application file and 21+21 firms of the testing file. The following methods were used for analyzing of these files:

- Discriminant analysis working with 8 input indices specified in Table 1,
- Logistic regression applying the same 8 input indices as preceding,
- Artificial neural network of 2 layers: 41 neurons in the 1st layer; 29 neurons in the 2nd layer (this structure can expressed as S=(8; 41; 29; 1). The Back Propagation algorithm was used. The input variables were the same as applied by the others methods.

It is obvious that predictions of corporate business performances in economic practice should be made by methods that demonstrate the highest rates of retroactive classification accuracy, as regards to firms whose economic status is known before the compilation of the input files. Such classification results are given in Table 2.

Table 2 **Classification results**

Method	Percentage of successfully classified firms			
	Application file (72 firms)		Testing file (21 firms)	
	Successful firms	Bankrupt firms	Successful firms	Bankrupt firms
Discriminate analysis	81,94	88,89	85,71	95,24
Logistic regression	95,83	94,44	90,48	100,00
Artificial neural network S = (8, 41, 29, 1)/E = 0,01	100,00	100,00	90,48	100,00

In Table 2 the training error, E, was established as the sum of the squares of the classification criterion deviations from the classification of those classes (groups) in which the input file firms were classed (i.e., 0 or 1).

The accuracy differences of classifying firms can be attributed to specific conditions of each method application:

Discriminate analysis: The multiple discriminate approach is based on the following main assumptions:

(a) the independent variables are multivariate normal

(b) the covariance matrices of the two groups (failed and non-failed) are equivalent [3].

Logistic regression: The logistic regression has the following advantages over MDA models:

(a) no assumptions need to be made regarding prior probabilities of failure and distribution of predictor variables

(b) the use of such models permits an assessment of the significance of the individual independent variables included in the model

(c) the models calculate the weight which each coefficient contributes to the overall prediction of failure or non-failure and produce a probability score, which makes the results more accurate [3].

Neural network: A neural network is characterized by the network architecture that is the number of hidden layers, the number of input nodes in each layer and how the nodes are connected. Since the number of hidden layers and the number of input nodes in each layer can affect the performance of a neural network, the appropriate network architecture for a particular data set can only be determined through experiments [5].

The Table 2 provides for test file result comparisons by applying both logistic regression and neuron networks. To a certain extent, it evidences the opinion that "despite the extensive literature, there seems to be no superior modeling method" [2]. As such, it is the user who decides his priorities:

- Logistic regression, which is less demanding as regards computation,
- Neural networks that can 'learn'.

CONCLUSION

The commencement and continuity of business relations with a firm depend on the knowledge whether the firm operates and continues operating successfully or is threatened by default. The methods of discriminate analysis, logistic regression and artificial neural networks were used to provide for such knowledge. These methods enable classification of firms into successful (profitable) or abortive (threatened by bankruptcy) by processing data of their financial statements. For practical applications, a method that can classify firms with the greatest accuracy is preferred. The accuracy was quantified by the percentages of correctly classified units (firms) with respect to the total number of units in the input files.

From this point of view, neural networks and logistic regression methods are on a par with each other, as their results are superior to those of the discriminant analysis method. It is to be assumed that the method of neural networks implies better possibilities of further development.

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Note: The responsible translator for English language is Borek Sousedík, Ostrava, Czech Republic.